Credit Shocks and Allocative Efficiency during a Financial Crisis*

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This paper studies the effect of credit supply shocks on aggregate labor productivity during a financial crisis. Using data on the universe of Italian manufacturing firms, we decompose aggregate productivity growth in changes in average productivity of incumbents, labor share reallocation among incumbents, entry, and exit. We estimate the impact of industry-specific exogenous credit supply shocks on each component. We find that credit supply tightening entails a drop in average productivity, counterbalanced by the reallocation of labor towards more productive firms, and no significant effect on the contribution of entry and exit to productivity growth. The offsetting response of reallocation is stronger in ex ante more financially constrained industries.

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1. Introduction

The 2007–08 financial crisis has been followed by an exceptional drop in output and productivity and a slow recovery in many developed

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countries. In recent years, a growing literature has tried to understand how credit restrictions affect GDP and aggregate productivity growth. In the years that follow a contraction in credit supply, firms reduce investment, employment, and innovation (Aghion et al. 2010; Chodorow-Reich 2014; Hall and Lerner 2010). Negative credit shocks increase firm exit (Caballero and Hammour 1994; Foster, Grim, and Haltiwanger 2016) and affect the selection of new entrants (Lee and Mukoyama 2015; Midrigan and Xu 2014). The impact of credit shocks on productivity could also go through the reallocation of production factors towards more productive uses (Banerjee and Duflo 2005) or by trapping them into low productivity firms (Gopinath et al. 2017).

Existing empirical studies based on firm-level data have separately documented each of these channels at work, but their relative importance and the overall impact of credit shocks on aggregate productivity is still an open question. In addition, firm-level studies rely on a sub-population of firms for which balance sheet data are available, typically incorporated firms. While these firms account for a large share of value-added and employment in the economy, they rarely allow one to fully observe firms' entry and exit and, importantly, the reallocation of workers. In this paper, using microdata from the universe of Italian manufacturing firms, we overcome these limitations to explore the different channels through which negative credit supply shocks affected Italian aggregate productivity growth between 2007 and 2015, a period enclosing two major recession episodes—the Great Recession (2008–09) and the European sovereign debt crisis (2012–13)—during which Italian per capita GDP dropped by nearly 11 percent at constant prices.

Our empirical strategy hinges upon the Melitz and Polanec (2015) aggregate labor productivity decomposition (MP decomposition, henceforth) into the growth of incumbent firms' productivity, the covariance between employment shares and productivity (which measures the extent of reallocation), and the contribution of entering and exiting firms. We apply the MP decomposition to each four-digit industry in manufacturing. These components are then used as dependent variables in a regression analysis, against industry-specific idiosyncratic credit supply shocks. We isolate credit supply shocks using detailed microdata from the Italian Credit Register. We first regress the growth rate of credit by each bank to each firm including a full set of firm-time and bank-time fixed effects. The former control for firm-level time-varying observed and unobserved heterogeneity, and allow us to purge our estimates from demand effects, which typically affect the dynamics of credit (Amiti and Weinstein 2018; Greenstone, Mas, and Nguyen 2020; Khwaja and Mian 2008)[1]. The latter represent the bank-specific credit supply shocks, which we then aggregate at the four-digit industry level using the share of credit of each bank in each industry.

Our results show that in our sample period the effect of credit supply restrictions on aggregate labor productivity growth at the industry level is driven by two offsetting responses. In line with previous findings (Aghion et al. 2010; Chodorow-Reich 2014; Hall and Lerner 2010; Manaresi and Pierri 2016), negative credit shocks depress aggregate productivity because of a negative direct effect on productivity at the firm level. Yet, negative credit shocks boost the reallocation of workers from the least productive to the most productive firms, exerting a positive effect on aggregate productivity. The effects are economically significant, and overall they offset each other. In our preferred specification, a one-standard-deviation lower credit supply shock leads to a negative contribution of average productivity by 3.6 percentage points and a positive contribution of reallocation of 2.4 percentage points. In both cases this represents about 60 percent of the observed average annual contributions of the two components to aggregate labor productivity growth. The credit supply shock has only a negligible effect on the contributions of exiting and entering firms to aggregate productivity growth. Our findings are robust to different sets of industry and time fixed effects, weighting schemes, and lag structures of the credit supply shock, and to different definitions of the idiosyncratic credit shock. Overall, our results show that the total effect of negative credit shocks on aggregate productivity is small.

[1]Estimating the credit shock conditional on firm*time fixed effects, we improve upon the procedure used in Greenstone, Mas, and Nguyen (2020) since we estimate bank*time fixed effects, i.e., the bank supply shocks conditional on firm*time unobservables and not industry*time, which may be less able to properly capture demand effects.

We document that these effects are heterogeneous across industries. We find that the effects of negative credit shocks on firm productivity and reallocation are concentrated in industries with a lower share of tangible capital and collateralized debt, consistent with recent evidence (Gopinath et al. 2017) showing that in those industries selection is stronger and factors of production are allocated best. The impact on reallocation is also higher in industries with low profitability, therefore having little possibility to substitute bank credit with internal finance. Moreover, the effects on reallocation are stronger in industries less exposed to import penetration, where low-productivity firms are sheltered from international competition and credit supply shocks could strengthen the selection process. Finally, we find that credit restrictions improve allocative efficiency especially in industries where product market shares are concentrated among top firms. These superstar firms are the most productive and face weaker credit constraints, and are therefore able to absorb the employment shares freed by firms hit hardest by the credit shocks.

Since the reallocation of workers occurs mostly at the local level, we replicate our empirical exercise at the level of local labor market ("sistema locale del lavoro", SLL).[2] The industry-level results are confirmed. A credit crunch has a negative effect on the incumbents' productivity but favors the reallocation of production factors towards more productive firms within the SLL; little effect can be detected on the entry and exit components. Overall, these results show that credit shocks affect productivity at different levels of aggregation, but propagate through similar channels. Interestingly, the offsetting effects on average firm productivity and allocative efficiency are more pronounced in areas where firms are more likely to face stronger financial constraints. We also find that the effects of credit shocks are stronger in SLLs with a greater incidence of exporters, which are more dependent on external finance due to the additional costs related to international trade.

Our findings contribute to the large literature on misallocation and productivity. Following the pioneering work of Hsieh and Klenow (2009), financial frictions as a source of misallocation have been the focus of a large literature, especially after the 2007–08 financial

[2]SLLs are conceptually similar to U.S. commuting zones.

crisis. Buera and Shin (2013) find that financial frictions prolong the adverse consequences of the initial resource misallocation. Moll (2014) suggests that financial frictions amplify total factor productivity (TFP) shocks in the short run, as firms find it difficult to overcome borrowing constraints, while Larrain and Stumpner (2012) find that a capital account liberalization decreases resources misallocation by improving the allocation of finance. Midrigan and Xu (2014) challenge these findings, suggesting that financial frictions play a limited role in the misallocation of resources, and they do so by creating a distortion in entry and exit rates. Recent work by Gopinath et al. (2017) finds that the decline in the real interest rate—often attributed to the euro convergence process—led to a significant decline in sectoral TFP in southern Europe, as capital inflows were allocated toward firms that had higher net worth but were not necessarily more productive. Using a unique data set covering the universe of Italian manufacturing firms, our contribution to this literature is to contemporaneously study the different channels by which credit shocks affect aggregate productivity growth. Our approach allows us to fully gauge the contribution of average firm productivity growth, allocative efficiency, and that of entering and exiting firms.

This paper is not the first to study the real effects of credit supply shocks on the Italian economy in the aftermath of the financial crisis. In recent work, Cingano, Manaresi, and Sette (2016) document a substantial drop in investment. Manaresi and Pierri (2016) show that a credit supply expansion increases both input accumulation and firms' ability to generate value-added for a given level of inputs, in this way enhancing productivity. More indirectly, Schivardi, Sette, and Tabellini (2022) find evidence of zombie lending in Italy during the financial and sovereign debt crises, but the real effects of this misallocation of credit are limited: sales, investment, and employment of non-zombie firms are hardly affected by the intensity of zombie lending. We add to this evidence by showing that credit restrictions had an overall limited effect on aggregate productivity: the negative direct effect of lower credit supply on firm-level productivity is mitigated by the positive impact on the reallocation of worker shares from low- to high-productivity firms, highlighting a channel by which credit-fueled recessions may be, at least in part, "cleansing" (Foster, Grim, and Haltiwanger 2016).

The paper is organized as follows. Section 2 presents the data used in this paper. Section 3 documents the dynamics of aggregate labor productivity and presents the results of the MP decomposition, providing some suggestive evidence on the connection between the dynamics of credit supply and the extent of reallocation and selection. Section 4 illustrates the estimation method of the credit supply shocks, and shows some related stylized facts. Section 5 discusses the empirical strategy. Section 6 illustrates the main results and presents some robustness checks and extensions. In Section 7 we enrich our results exploring some dimensions of heterogeneity across industries. In Section 8 we replicate our baseline exercise at the level of local labor market. Section 9 concludes.

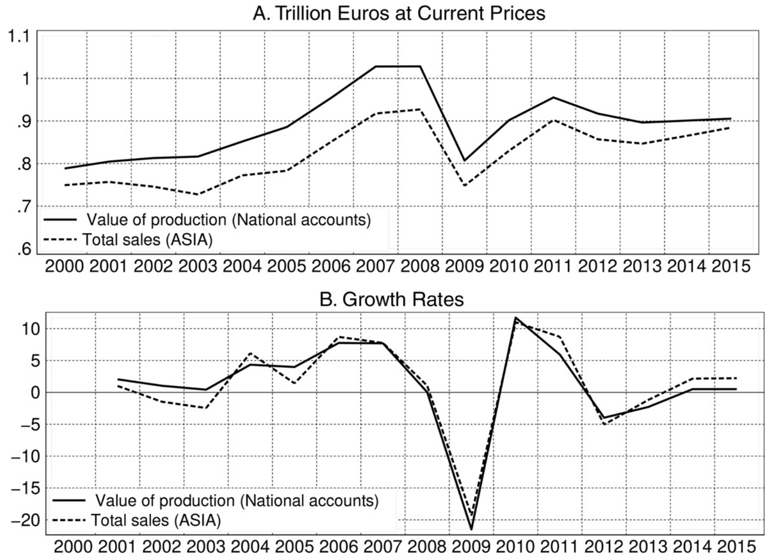
2. Data

The paper relies on two different data sources. The first is a unique firm-level data set that covers the universe of manufacturing firms from 2000 to 2015, although the focus of our empirical analysis will be on the crisis period 2007–15. The data set has been jointly developed by the Bank of Italy and the Italian National Statistical Agency (Istat); it combines the information of the Italian Register of Active Firms (ASIA) with data retrieved from statistical, administrative, and fiscal sources. The data set contains information on firms' location, incorporation date, industry classification (NACE Rev. 2), number of employees, and sales.[3] We deflate sales to 2010 prices, using sector-level price indices. We exploit administrative information to directly observe entry and exit of firms, and we are able to single out and control for extraordinary events in the life of a firm—such as mergers and acquisitions—which will otherwise introduce noise in the definition of such events.

The quality of our micro-aggregated data can be gauged by comparing them with National Accounts data. Panel A of Figure 1 compares the value of production from National Accounts with the total value of sales from the ASIA data set over a 16-year time

[3]See Abbate, Ladu, and Linarello (2017) for a detailed description of the data set. An employee in our data set is defined as a person who works for a firm on the basis of a contract of employment and receives compensation in the form of wage or salary.

Figure 1. Comparison between National Accounts and ASIA Data Set



Note: Panel A shows the value of production from National Accounts (solid line) and total sales from Istat (dashed line), both measured at current prices. Panel B shows the corresponding growth rates.

span.[4] The two series display very similar patterns, with a very high correlation (.933).[5] As shown in panel B, the similarity with the National Accounts also emerges when looking at the growth rates (the correlation is .969).

The second data source we rely on is the comprehensive Italian Credit Register, a database owned by the Bank of Italy, which contains data on all individual bank-borrower relationships with an exposure of at least 75,000 euros until 2008, and 30,000 since 2009.[6]

[4]Both series are evaluated at current prices, in order to exclude the discrepancies deriving from the use of price deflators at different levels of disaggregation.

[5]The National Account series shows values mostly larger than the ASIA data, since the former includes estimates of the underground economy and illegal workforce.

[6]To avoid that results are biased by this change in thresholds, we have dropped all the relationships with an exposure below 75,000 euros. Our results are robust

The Credit Register lists outstanding balances of loan amounts at the lender-borrower level aggregated into three categories—overdraft loans, term loans, and loans backed by receivables—and it also flags non-performing loans. Banks routinely use the Credit Register to assess the creditworthiness of current and prospective borrowers, which ensures a high quality of the data. Unique identifiers of banks and borrowers allow us to track them over time. The Credit Register contains both granted (committed) credit and actually used (drawn) credit. We focus on the former, as it represents a better measure of credit supply, while the latter is heavily influenced by borrowers' decisions to use available credit.[7]

During our sample period, Italian manufacturing shrank significantly. The long-standing downward trend in the number of manufacturing firms and employees—dating back to the late 90s—was further exacerbated by the two recessions that hit the Italian economy: the Great Recession (2008–09) and the European sovereign debt crisis (2012–13). Table 1 reports descriptive statistics of the firms in our sample. Starting in 2007, the number of firms declined every year: in 2015 there were about 60,000 fewer firms than in 2007. As a consequence, the number of employees dropped by more than 500,000 units. Average firm size—measured in terms of employees per firm—remained roughly constant. Sales dropped sharply in correspondence with the two recession episodes. Aggregate labor productivity—measured as real sales per worker[8]—decreased during

to the inclusion of the credit relationships below this threshold; results are available upon request.

[7]Our results are robust to using drawn rather than granted credit. Results are available upon request.

[8]We claim that using sales per worker as a measure of labor productivity (instead of value-added per worker, for example) does not undermine our results. First, sales per worker is more suitable for the decomposition exercise that we are going to perform: expressing productivity in logs (as required by the MP decomposition) would imply a substantial information loss if using value-added, which is often negative especially during recessions. Second, in literature it is not uncommon to use sales per worker as a valid alternative for measuring labor productivity, as in Bartelsman, Haltiwanger, and Scarpetta 2013). Third, despite displaying some differences, in Italy aggregate value-added per worker and sales per worker broadly share similar dynamics, as shown by Linarello and Petrella (2017).

Table 1. Descriptive Statistics for Manufacturing, Years 2007–15

	No. Firms	No. Employees	Avg. Size	Sales	Sales per Worker
2007	447,206	4,170,744	9.33	944,626	226,489
2008	441,744	4,173,805	9.45	918,000	219,943
2009	426,710	3,992,769	9.36	766,893	192,071
2010	416,022	3,867,436	9.30	830,263	214,680
2011	414,430	3,873,660	9.35	867,249	223,884
2012	406,694	3,799,113	9.34	814,082	214,282
2013	398,092	3,717,963	9.34	806,218	216,844
2014	388,633	3,662,740	9.42	826,145	225,554
2015	383,407	3,660,049	9.55	854,755	233,536

Note: The table displays summary statistics for the data used in the analysis. The first column reports the number of firms in the manufacturing sector, while the second shows the total number of employees. The third column shows the average firm size, computed as the number of employees per firm. The last two columns report the total sales expressed in million euros and our measure of productivity (real sales per worker). Both sales and sales per worker have been deflated to 2010 values.

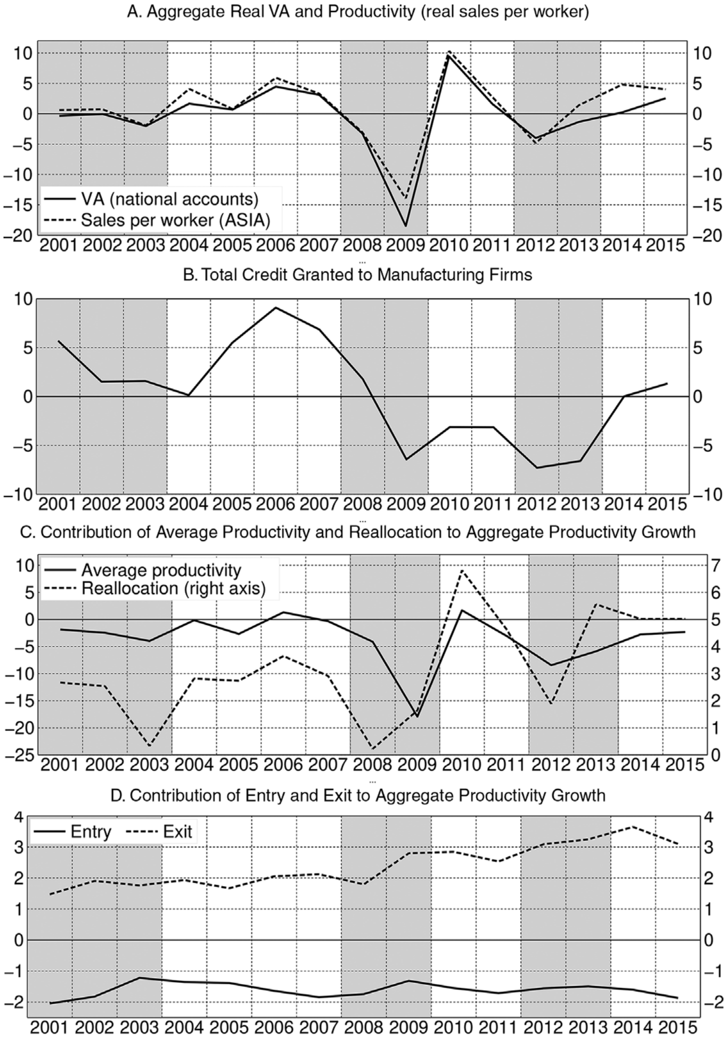
economic downturns. The double-dip recession had enduring consequences on Italian aggregate labor productivity, which in 2015 was only slightly above its 2007 levels.

3. The Dynamics of Aggregate Productivity and Its Components

In this section we sketch the main trends of aggregate manufacturing labor productivity in Italy, focusing on the driving forces that have shaped its dynamics, and hinting at potential links with the fluctuations of credit supply. Figure 2 shows the evolution of the main series that we use in the empirical analysis.

Value-added in manufacturing has experienced a 7.1 percent drop between 2000 and 2015. As shown in panel A, the sector experienced a contraction in roughly half of the observed years, while not attaining a consistently fast-paced growth in the remaining ones. The most substantial drop in value-added was experienced in correspondence with the the global financial crisis (2008–09), followed

Figure 2. Italian Manufacturing, Growth Rates, Years 2001–15



Note: In each panel shaded areas indicate recession periods defined as year with negative GDP growth rate in the manufacturing sector. Panel A shows the annual growth rate of real value-added from National Accounts (solid line) and real sales per worker from Istat (dashed line). Panel B shows the annual growth rate of total credit granted to manufacturing firms from Credit Register. Panels C and D show the contribution to aggregate productivity growth of each component of the MP decomposition; see Section 3 for more details.

by a brief rebound and another (more moderate) contraction during the sovereign debt crisis (2012–13).

The dynamics of manufacturing value-added should be read in parallel to the chart displayed in panel B, depicting the evolution of total credit granted to manufacturing firms. Bank loans have grown at positive rates until the global financial crisis: during the 2001–03 recession, which didn't have a financial nature, the growth of credit remained positive and then increased in magnitude until 2006. After the outbreak of the crisis, the massive liquidity drought in interbank markets mirrored the rapid shrinkage of credit; the pace of contraction slowed down during the partial recovery of 2010, but another and more severe period of credit restriction was fostered by the sovereign debt crisis. A faint recovery emerged from 2014 on.

To understand the impact of credit shocks on the contribution of the key different drivers of aggregate labor productivity, we exploit the decomposition proposed by Melitz and Polanec (2015) as a dynamic extension of the widely used Olley and Pakes (1996) decomposition. This allows us to distinguish between the efficiency gains generated by the reallocation of resources towards the most productive firms (measured by the OP covariance term), those arising from the productivity growth of individual firms (captured by the average firm productivity term), and those deriving from the process of firm entry and exit.

We define aggregate labor productivity as the average of firm-level log productivity, weighed by each firm's share of employees. We then divide firms into three groups: entrants (E), exiting (X), and incumbent firms (S). Considering two consecutive time periods, it is possible to express the aggregate productivity of the first period (Φ_1) as the weighted average of the productivity of the firms that survive and the one of the firms that exit the market; analogously, the aggregate productivity of the second period (Φ_2) can be expressed as the weighted average of the productivity of the firms that survived and the one of the firms that have entered the market:

$$\Phi_1 = \Phi_{S1}\omega_{S1} + \Phi_{X1}\omega_{X1} \tag{1}$$

$$\Phi_2 = \Phi_{S2}\omega_{S2} + \Phi_{E2}\omega_{E2}, \tag{2}$$

where Φ_{gp} is the aggregate productivity of group g in period p, and ω_{gp} is the share of employees in each group.

The difference between Φ_2 and Φ_1 returns the variation in aggregate productivity:

$$\Phi_2 - \Phi_1 = (\Phi_{S2} - \Phi_{S1}) + \omega_{E2}(\Phi_{E2} - \Phi_{S2}) + \omega_{X1}(\Phi_{S1} - \Phi_{X1}), \tag{3}$$

where the first term represents the productivity variation for the incumbent firms that are active on the market in both periods; the second is the contribution of entrants, which is positive (negative) if their productivity is higher (lower) than the one of the incumbent firms; the third is the contribution of firms that exit the market, which is positive (negative) if their productivity is lower (higher) than the one of the incumbents.[9]

Making use of the Olley and Pakes (1996) decomposition, the term $(\Phi_{S2} - \Phi_{S1})$ can be further decomposed in the variation of the incumbents' average productivity and the one of the covariance between incumbents' productivity and the share of employees, capturing the intensity of the reallocation process. To sum up, the variation of aggregate productivity can be expressed as the sum of the following four components:

$$\begin{aligned} \Phi_2 - \Phi_1 = \underbrace{\Delta\bar{\varphi}_S}_{\text{Avg. prod.}} + \underbrace{\Delta\text{Cov}_S}_{\text{Reallocation}} + \underbrace{\omega_{E2}(\Phi_{E2} - \Phi_{S2})}_{\text{Entry}} \\ + \underbrace{\omega_{X1}(\Phi_{S1} - \Phi_{X1})}_{\text{Exit}}. \end{aligned} \tag{4}$$

Figure 2 shows the evolution of the four components over time. Aggregate labor productivity has a similar dynamics as manufacturing value-added (panel A). As panel C shows, reallocation has

[9] For sake of simplicity, here we have only referred to three groups (entering, exiting, and incumbent firms). When we apply the decomposition, however, we define additional groups, capturing the contribution of false entry/exit (in the spirit of Geurts and Van Biesebroeck 2016) and extraordinary events. That is intended to provide both an exact decomposition and a neater definition of phenomena: the demographic components will measure the contributions of the firms that are truly entering or exiting the market, and the data on incumbents will be net of those incumbents that have undergone extraordinary operations in one of two adjacent years. Overall, these additional components typically account for a small share of the variation in aggregate productivity.

Table 2. Melitz–Polanec Decomposition of the Dynamics of Italian Aggregate Labor Productivity in Manufacturing

		Incumbents		Demography	
	Total Productivity	Average Productivity	Reallocation	Entry	Exit
2008	−3.05	−4.11	0.22	−1.74	1.80
2009	−13.95	−17.93	1.64	−1.31	2.80
2010	10.33	1.70	6.82	−1.55	2.84
2011	2.74	−3.04	4.63	−1.71	2.53
2012	−4.83	−8.44	1.89	−1.55	3.09
2013	1.41	−5.89	5.56	−1.49	3.25
2014	4.80	−2.76	5.02	−1.60	3.65
2015	4.02	−2.30	5.02	−1.87	3.10

Note: The table displays the aggregate productivity growth (first column) and the contribution of each component according to the MP decomposition performed as described in Section 3. Productivity is measured as real sales per worker. The sum of the single components (columns 2–5) may not add up to the total variation (column 1), since the contribution of extraordinary events and false entry/exit is not displayed; overall, the impact of these components on the dynamics of aggregate productivity is negligible.

always provided a positive contribution to aggregate labor productivity, partially offsetting the dynamics of average firm productivity, whose contribution was negative in 13 out of 15 years (see also Table 2). The contribution of reallocation moderately rose until 2006, and then momentarily slowed down, just before peaking in the wake of the two crisis episodes. Interestingly, the rise in the reallocation component mirrors the drop in credit supply.

Panel D displays the contribution of entry and exit. The contribution of entering (exiting) firms is always negative (positive), since their aggregate productivity in the first (last) year of life is typically lower than the one of incumbents.[10] The entry component fluctuates

[10]The negative contribution of the entry component stems from our definition of newborn firms as those in their first year of life, which is a direct consequence of the year-on-year decomposition adopted. One-year-old firms generally show a lower revenue per worker than incumbents for a variety of reasons—including, for example, that they have not yet undergone a selection process, that they

in a narrow band with small differences across periods. The exit component remains remarkably stable during the first part of our sample, even during the first recession episode of 2001–03. After the global financial crisis, however, its contribution progressively increases.

Overall, this broad picture provides suggestive evidence of a link between credit supply and key components of aggregate labor productivity, with potentially conflicting effects on aggregate labor productivity dynamics. In the remainder of this paper, we exploit our granular data to test this hypothesis.

4. The Credit Supply Shock: Estimation and Basic Facts

To identify bank-specific credit shocks, we apply the methodology proposed by Greenstone, Mas, and Nguyen (2020) on loan-level microdata from the Italian Credit Register data. We make an important improvement, though: since we can observe data on individual bank-firm relationships, we estimate the bank-specific credit shocks conditional on a full set of firm*time fixed effects, to control for firm observable and unobservable time-varying characteristics, including demand for credit, firm riskiness, etc. This provides a better control for these crucial features of credit dynamics than the inclusion of industry*time fixed effects.

We obtain credit supply shocks estimating the following model:

$$\Delta \ln(L_{bit}) = \alpha_{bt} + \gamma_{it} + \epsilon_{bit}, \tag{5}$$

where $\Delta \ln(L_{bit})$ is the log change in credit granted by bank b to firm i at time t. $\alpha_{b,t}$ are a set of bank*time fixed effects and γ_{it} are a set of unit of firm*time fixed effects. In practice, model (5) compares the growth of credit from different banks lending to the same firm in any year. The firm*time fixed effects control for changes in demand and economic conditions at the firm level in each year, while the bank*time fixed effects $\alpha_{b,t}$ are the components of the credit dynamics that are common to each bank b across the credit

tend to compress their prices to acquire market shares (Foster, Haltiwanger, and Syverson 2016), or that revenues materialize with some lag with respect to production. If considered over a longer time horizon, young firms stand out as a more dynamic component and account for a relevant fraction of overall productivity growth (Haltiwanger et al. 2017).

relationships observed, and can therefore be interpreted as bank-specific, idiosyncratic credit supply shocks.[11]

The set of bank-time fixed effects, $\alpha_{b,t}$, identifies a supply-induced change in credit under the assumption that firms do not have bank-specific demand for credit, so that the set of firm-time fixed effects fully control for changes in demand and in the riskiness and economic prospects of the firms. Under this condition, these shocks are uncorrelated with any characteristics of the firms and of the markets in which the banks operate. This assumption could be violated if a bank specialized in financing a specific category of firms. Amiti and Weinstein (2018) and Greenstone, Mas, and Nguyen (2020) argue that bank*time fixed effects can still be interpreted as a measure of credit supply, even if this assumption were violated. Furthermore, controlling for time-varying fixed effects at the firm level makes the violation of such assumption less probable than if we were estimating bank shocks conditional on industry*time fixed effects alone.

To provide evidence supporting the correct identification of the bank shocks, we test their correlation with key bank balance sheet characteristics which are regarded as major drivers of banks' propensity to lend. We regress the estimated bank shock relative to year t on bank-level characteristics measured as of December of year $t-1$.[12] Results, shown in Table 3, indicate that banks with higher capital, lower interbank funding, and higher liquidity supply more credit. Credit supply is also negatively correlated with a higher share of (gross) non-performing loans. Despite being limited to conditional correlations, these results are reassuring, since they indicate that banks with a stronger (measured by capital and the bad loans ratio), more liquid, and less volatile funding structure (less interbank funding) are associated with higher values of the credit supply shock,

[11] This approach to identify the bank-lending channel at the firm level has been first proposed by Khwaja and Mian (2008). Barone, de Blasio, and Mocetti (2018) and Manaresi and Pierri (2016) apply a similar technique to estimate credit supply shocks for the Italian economy.

[12] We use data from Supervisory Reports. For these tests we exclude foreign banks for which we observe incomplete balance sheet information, and also exclude the year 2015, because of a major change in the reporting of supervisory information occurring in 2014, when supervision moved from the national central banks to the European Central Bank.

Table 3. Credit Supply Shocks and Bank Balance Sheet Characteristics

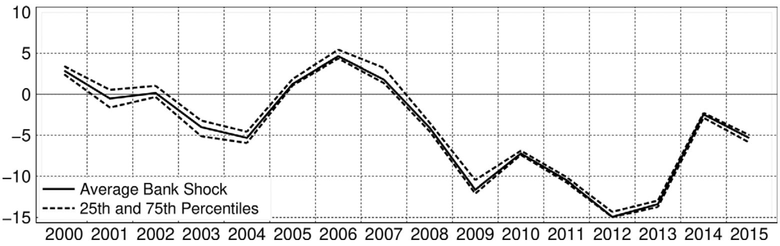
	(1)	(2)	(3)
Capital	0.186**	0.193**	0.131
	(0.0886)	(0.0879)	(0.0946)
Liquidity	0.238***	0.188***	0.205***
	(0.0547)	(0.0603)	(0.0609)
ROA	–0.0246	–0.362	–0.0184
	(0.698)	(0.710)	(0.660)
Interbank	–0.138*	–0.164*	–0.173*
	(0.0822)	(0.0894)	(0.0887)
Non-performing	–0.729***	–0.793***	–0.689***
	(0.137)	(0.134)	(0.120)
Size	0.00475*	0.00418	–0.00132
	(0.00248)	(0.00259)	(0.00314)
Mutual			–0.0384**
			(0.0154)
Constant	–0.113***		
	(0.0280)		
Year FE	N	Y	Y
Observations	2,815	2,815	2,815
R^2	0.058	0.085	0.091

Note: The table displays the results from a regression of the bank-level credit supply shock (the $\hat{\alpha}_{bt}$, from model (5)) against a number of bank balance sheet variables. *Capital* is the ratio of equity to total assets, *Liquidity* is the ratio of cash and government bonds to total assets, *ROA* is the ratio of profits (losses) to total assets, *Interbank* is the ratio of interbank deposits including repos to total assets, *Non-performing* is the ratio of gross non-performing loans to total assets, *Size* is the log of total assets, *Mutual* is a dummy equal to one if the bank is mutual. Standard errors clustered at the bank level are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

suggesting higher credit supply relative to other banks. These results are also consistent with previous findings on the bank lending channel in Italy (di Patti and Sette 2016) and in other countries (Khwaja and Mian 2008; Iyer et al. 2014; Jiménez et al. 2012).

Since most of the following analyses will be performed at the industry (four-digit NACE Rev. 2) level, the bank-specific shocks in (5) need to be aggregated to obtain a measure of the evolution of credit supply at the industry level. This will essentially be an average

Figure 3. Credit Supply Shock



Note: The solid line shows the average credit supply shock CSS_t computed as simple average across industries in a given year; the dotted lines represent the 25th and 75th percentile of the CSS_{jt}. See Section 4 for more details on the calculation of the credit supply shock.

of the bank shocks, weighted by the within-industry market share of each bank. More formally, the credit supply shock is computed as

$$CSS_{jt} = \sum_{b} \theta^{j}_{b,2007} \widehat{\alpha}_{bt}, \tag{6}$$

where $\theta^{j}_{b,2007}$ is the market share of bank b in industry j in 2007. These shares are computed aggregating the loans in the Credit Register at the industry level. Since the bank shocks α_{bt} are identified up to a constant scaling factor, the credit supply shock cannot be attached an absolute quantitative interpretation. The differences among banks supply shocks both cross-sectionally and over time are, instead, preserved.[13] From Figure 3 it is apparent that the propensity of financial intermediaries to lend declined dramatically in correspondence with the two recessions; the intensity of the drop was even greater after the sovereign debt crisis than after the global financial crisis.[14]

[13]For the sake of clarity, suppose that we estimate a credit supply shock of 5 and –5 for a given sector in time t and $t+1$, respectively: we are not able to state whether credit supply actually expanded or shrunk in the two periods (since it is not possible to derive the reference level), but we can assert that the growth rate of credit supply decreased by 10 percentage points; the same kind of comparison is valid across sectors, within a certain year.

[14]See di Patti and Sette (2016) and Bofondi, Carpinelli, and Sette (2018) for evidence of the impact on credit supply of the post-Lehman and the sovereign shocks, respectively, in Italy.

5. Empirical Strategy

Our aim is to investigate the effect of credit supply on the components of aggregate labor productivity growth documented in Section 3. To do that, we first apply the MP decomposition to each of the 177 four-digit industries represented in our sample,[15] and then check whether the credit shocks estimated in Section 4 have an impact on the contributions of average productivity, reallocation, entry, and exit.

The results of the MP decomposition are shown in Table 4, which reports the productivity decomposition at the sector level (for sake of compactness, results are presented at the two-digit level). Despite the large across-sector heterogeneity in the size of the displayed components, in the crisis period, all sectors share some broad common patterns: while the contribution of average productivity is always negative, the one of reallocation and net demography (the sum of entry and exit) is always positive. During the period before the crisis, the contribution of reallocation and demography is smaller in size and occasionally negative.[16]

In its most general form, the specification adopted for most of the analyses presented below is the following:

$$y_{jt} = \beta CSS_{jt} + \gamma_t + \delta_j + \varepsilon_{jt}, \tag{7}$$

where y_{jt} is the dependent variable of interest at the industry level (four-digit): it will correspond either to the growth rate of labor productivity or to one of the four contributions outlined in Equation (4); CSS_{jt} is the credit supply shock, as defined in Equation (6); γ_t are year fixed effects; δ_j are a set of industry fixed effects; ε_{jt} is an error term. Standard errors are clustered at the industry level to account for serial correlation. The coefficient of interest is β, capturing the effect of credit supply shocks.

[15]Our original data cover 223 industries, but we exclude from our analysis those with less than 100 firms to ensure that the MP decomposition does not reflect the behavior of a few large firms in a given sector. The excluded industries account for less than 0.6 percent of firms and 4 percent of employees.

[16]Results are not displayed, but are available upon request.

Table 4. Melitz–Polanec Decomposition by Sector

Sector	Total Productivity	Incumbents: Average Productivity	Incumbents: Reallocation	Demography: Entry	Demography: Exit
10	−0.17	–3.19	2.28	–2.28	2.93
11	−0.31	–2.98	2.12	–1.76	2.02
13	0.70	–6.92	4.55	–1.25	4.16
14	−0.09	–7.04	3.52	–4.43	7.40
15	0.01	–5.95	4.50	–3.06	4.42
16	−1.11	–6.11	1.76	–0.67	3.95
17	0.57	–5.41	4.69	–0.61	1.52
18	−0.53	–5.84	3.21	–0.95	3.16
19	−1.47	–4.30	5.54	–0.67	0.89
20	−0.97	–4.03	2.65	–0.55	0.89
21	2.60	–1.54	3.85	0.06	0.03
22	−0.05	–5.18	4.42	–0.69	1.62
23	−1.32	–6.81	3.77	–0.74	2.33
24	−1.58	–5.26	3.46	–0.46	0.84
25	−0.13	–5.13	3.49	–1.07	2.44
26	2.35	–5.80	6.51	–0.55	0.71
27	0.76	–5.16	4.31	–0.73	1.46
28	−0.03	–4.74	3.96	–0.46	0.92
29	1.28	–6.24	6.17	–0.36	0.58
30	1.69	–9.38	10.20	–1.36	2.25
31	−0.94	–6.80	3.72	–1.07	3.19
32	−1.06	–4.10	1.90	–1.35	2.78
33	−0.90	–5.42	2.91	–1.57	3.29

Note: The table shows the simple averages across four-digit industries over the results of the year-on-year MP decomposition, performed as described in Section 3. Productivity is measured as real sales per worker. Aggregate productivity is defined as the weighted average of firm-level log productivities. The sum of the single components may not add up to the total variation, since the contribution of extraordinary events and false entry/exit is not displayed; overall, the impact of these components on the dynamics of aggregate productivity is negligible.

Estimates of Equation (7) measure the within-industry effects of credit supply shocks. A natural question is whether within-industry forces account for a relevant fraction of overall labor productivity dynamics. To address this issue, note that all the components of the MP decomposition for aggregate productivity growth can be expressed as the sum of a within-industry term and a between-industry term (formulas available in Appendix A).[17] While the within-industry terms gauge the intra-industry forces that contribute to aggregate productivity growth, the between-industry ones capture the role of relative variations of the labor shares and productivity across industries.

Table 5 shows the decomposition of the reallocation, exit, and entry terms in their within and between industry components; for each variable, the third column reports the incidence of the within term on the total. The results show that the within forces are significantly more relevant than the between ones in determining aggregate productivity growth: on average, the within component accounts for more than 80 percent of the reallocation and exit terms, and for more than 70 percent of the entry one.[18] This evidence confirms that focusing on within-industry effects entails the loss of a very small fraction of overall productivity growth. In one of the extensions, we will replicate the same exercise using local labor markets ("sistemi locali del lavoro," SLL) as the unit of aggregation; in that case, the incidence of the within component is even higher, accounting for more than 90 percent of reallocation and exit, and for 85 percent of entry.

5.1 Testing the Validity of the Research Design

The validity of our research design relies on the assumption that industries more exposed to banks with larger credit supply changes do not exhibit systematically larger or smaller shocks to labor productivity for reasons different from changes in credit supply. To explore the validity of our design, following Greenstone, Mas, and Nguyen (2020), we perform several tests.

We start by comparing the characteristics of four-digit industries more and less exposed to the credit supply shocks. If industries

[17] Except average productivity, which can be directly obtained as a linear combination of the single industry-specific terms.

[18] The weight of the within-sector component of reallocation depends on the granularity of the data; more precisely, it is inversely proportional to the level of disaggregation at which the decomposition is applied. At the two-digit sector level, the within component has a greater incidence in all cases (≈85 percent for reallocation and exit, ≈80 percent for entry).

Table 5. Within and Between Components of the MP Decomposition

	Reallocation			Entry			Exit		
	With.	**Betw.**	**% With.**	**With.**	**Betw.**	**% With.**	**With.**	**Betw.**	**% With.**
2008	0.16	0.06	72.63	−1.29	−0.45	74.36	1.57	0.23	87.25
2009	3.66	−2.02	223.07	−0.95	−0.36	72.48	2.22	0.58	79.40
2010	4.25	2.57	62.28	−1.12	−0.42	72.59	2.29	0.55	80.55
2011	3.28	1.35	70.83	−1.19	−0.52	69.39	2.08	0.45	82.09
2012	1.91	−0.02	101.21	−1.08	−0.48	69.40	2.61	0.48	84.60
2013	4.32	1.25	77.59	−0.99	−0.50	66.75	2.61	0.64	80.23
2014	3.70	1.31	73.86	−1.14	−0.47	70.95	3.03	0.62	83.10
2015	4.05	0.97	80.74	−1.35	−0.52	72.35	2.54	0.56	81.88
2008–15 Mean	3.17	0.68	82.25	−1.14	−0.46	71.09	2.37	0.51	82.18

Note: The table shows for each component of the MP decomposition indicated at the top of the columns the contribution of the within and between four-digit industry variations, computed according to the procedure described in the appendix. The sum of the within and between components adds to the reallocation, exit, and entry components in Table 2.

Table 6. Balance Table of Industry Characteristics

	Above CSS Median in the 2008–15 Period (1)	Below CSS Median in the 2008–15 Period (2)	p-value of the Difference (3)	Difference Above-Below, Within Two-Digit Sector (4)	p-value of the Within-Sector Difference (5)
Number of Firms Growth, Average 2001–07	–0.006	–0.009	0.656	0.002	0.694
	(0.004)	(0.004)		(0.006)	
Sales Growth, Average 2001–07	0.018	0.028	0.302	–0.006	0.562
	(0.007)	(0.007)		(0.011)	
Employment Growth, Average 2001–07	–0.000	0.007	0.174	–0.005	0.400
	(0.004)	(0.004)		(0.006)	
Wage Growth, Average 2001–07	0.033	0.030	0.236	0.004	0.129
	(0.002)	(0.002)		(0.002)	
Import Competition, 2004–07 Average	0.284	0.267	0.653	0.034	0.356
	(0.026)	(0.025)		(0.037)	
Top 20 Firms' Market Share, 2004–07 Average	0.624	0.533	0.009***	0.117	0.001***
	(0.024)	(0.024)		(0.036)	

Note: Industries (NACE four-digit) are divided in two groups according to their credit supply shock being above or below the median over the period 2008–15. Averages and differences in means for some key variables are displayed in each row. Column 4 is obtained from a regression of each of the row variables on a dummy variable for the industries above the credit supply shock median and a set of fixed effects at the NACE two-digit sector level. Import competition is defined as the ratio between imports and domestic absorption. Standard deviations in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

more exposed to shocks are systematically different from the less-exposed ones across key observable characteristics, our identifying assumption is less likely to hold. Table 6 reports summary statistics of industry characteristics measured in the pre-crisis period, based on whether the credit supply shock is above or below the median.[19] The first two columns show the simple raw means; column 4 shows the difference between the two, controlling for two-digit industry fixed effects. Columns 3 and 5 report the p-values from the test on equality of means. Overall, all characteristics are balanced, with one exception: the *pre-crisis* average market share of the top 20 firms (i.e., concentration). Hence, industries that are more exposed to the credit supply shock display a somewhat higher ex ante market concentration.

As shown in Section 4, the bank-specific shocks are by construction uncorrelated with any characteristics of the firms and the markets in which the banks operate; moreover, the market shares used to aggregate the bank-specific shocks are predetermined, in order to avoid incorporating in the shock the strategic decisions of the banks, potentially driven by the performance of firms within a given industry. Finally, the inclusion of industry fixed δ_j effects in our baseline regression are also intended to control both for the differences in pre-existing characteristics between industries and to address additional concerns related to potential omitted variables correlated to the economic and credit cycles.

As a further check, we test whether banks with more negative credit supply shocks systematically sort into certain sectors. We first check if the estimated credit supply shock is correlated to the characteristics of the firms in a given four-digit industry. To do that, we regress the credit supply shock in Equation (6) against the industry-level employees-weighted average of the firm fixed effects in Equation (5). As shown in column 1 of Table 7, the estimated coefficient is very close to, and not significantly different from, zero. We then regress the fixed effect of each bank b against the one of its competitors, defined as the lending-weighted average of the fixed effects of all

[19]The variables that we consider are the growth rate between 2001 and 2007 of number of firms, sales, employment, wage, import competition (the ratio between imports and domestic absorption), and product market concentration (the share of sales of the 20 largest firms within each four-digit industry).

Table 7. Tests for Bank Sorting

	Industry-Level Data (1)	**Bank-Level Data (2)**
Dependent Variable:	Credit Supply Shock	Bank Fixed Effect
Average Firm Fixed Effect	0.030	
	(0.205)	
Average Fixed Effect of Competitor Banks		0.118
		(0.168)
Year FE	Y	Y
Observations	1,415	3,773
Within R^2	0.000	0.000

Note: Standard errors in parentheses. Column 1 estimates an OLS regression on yearly industry-level data (NACE four-digit). The dependent variable is the credit supply shock, as defined in Equation (6). The explanatory variable is the employees-weighted average of the firm fixed effects in Equation (5). The data on employees needed to compute the weighted average belong to the INPS data set of all Italian firms with at least one employee. As a consequence, the fixed effects of firms with no employees have been excluded from this analysis. Column 2 displays the results of an OLS regression of each bank b's fixed effect on the average fixed effect of its competitor banks in the industries where it operates. To compute this explanatory variable, we calculate the lending-weighted average bank fixed effect in every industry (excluding bank b) and then aggregate these averages to the bank level, weighting by the share of bank b's lending in the industry.

the banks operating in the industries where b is present. Column 2 of Table 7 shows that the coefficient is not significantly different from zero, suggesting that banks displaying comparable supply shocks do not systematically sort into the same industries.

6. Industry-Level Results

We start by testing if and to what extent credit shocks affect each of the four components of the MP decomposition at the four-digit industry level, in the crisis and post-crisis years (2007–15). Results are shown in Table 8, and are arranged so that each row contains the estimates of β associated with a given dependent variable. Different

Table 8. Industry-Level Results

Dependent VARs	Independent VAR	(1)	(2)	(3)	(4)
Average Productivity	CSS_t	0.816***	1.244***	1.548***	0.722***
		(0.290)	(0.300)	(0.404)	(0.261)
Reallocation	CSS_t	–0.730**	–0.842**	–0.873*	–0.568*
		(0.357)	(0.366)	(0.485)	(0.325)
Entry	CSS_t	0.048	0.072	0.019	0.079
		(0.061)	(0.068)	(0.048)	(0.084)
Exit	CSS_t	0.059	–0.098	–0.013	–0.135
		(0.109)	(0.104)	(0.119)	(0.110)
Aggregate Productivity	CSS_t	0.203	0.423	0.805	0.118
		(0.331)	(0.429)	(0.615)	(0.256)
Year FE		Y	Y	Y	N
NACE Two-Digit FE		Y	Y	N	N
NACE Four-Digit FE		N	N	Y	N
Year*NACE Two-Digit FE		N	N	N	Y
Weighted		N	Y	Y	Y
Observations		1,416	1,416	1,416	1,408

Note: The table displays the estimates of the coefficient β in model (7). Each column uses a different set of fixed effects indicated at the bottom of the table and each row uses a different dependent variable, corresponding to each component of the MP decomposition. "Weighted" indicates that regressions are weighted using four-digit industry employment weights. Standard errors clustered at the industry (NACE four-digit) level in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

columns correspond to different specifications, depending on the sets of industry and time fixed effects included.

The first row shows that credit supply shocks have a significant impact on firm-level productivity: during a financial crisis, industries experiencing a stronger contraction in credit supply suffer a significant drop in the average productivity component of the industry-wide productivity growth. This result is in line with intuition and with other empirical findings on Italy (Manaresi and Pierri 2016). Coefficients increase in both magnitude and significance when we weigh observations by the number of employees in each industry to provide an estimate of the aggregate impact of the bank shock. The result is robust to the inclusion of finer industry fixed effects and of a set of sector-year dummies to control for different business cycles at the sector level (columns 3 and 4). The effects are economically significant: a one standard deviation fall in credit supply generates a 3.60 percentage point negative contribution of average productivity, which is about 60 percent of the observed negative contribution (–5.75) over the period 2008–15 (calculation from the preferred specification shown in column 2).

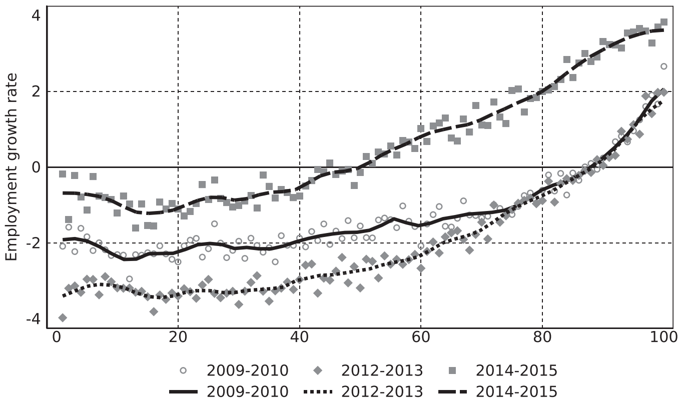
The second row shows that credit supply shocks affect aggregate productivity also through the reallocation component: when credit supply shrinks, the contribution of reallocation to the dynamics of aggregate industry productivity increases. Also in the case of reallocation, the estimated effect is economically significant: a one standard deviation negative bank shock is associated with a positive contribution of reallocation to aggregate productivity growth of 2.44 percentage points (based once more on the preferred specification of column 2), which is a sizable number compared with the observed contribution over the same period (3.97).

These results signal that during a financial crisis the allocation of production factors (labor, in our case) improves in industries where credit supply shrinks more severely. Since in our framework factor allocation is measured in terms of labor shares, this improvement could either reflect the fact that more productive firms get bigger (i.e., hire more workers) at the expenses of the less productive firms that shrink, or that more productive firms lay off workers at a lower rate: both of these scenarios imply an expansion of the labor shares held by more productive firms. Which of these two situations prevails ultimately depends on the cyclical conditions of the economy. Figure 4 plots the average employment growth of surviving firms in a selected number of years, by the percentile of the productivity distribution they belong to. In all cases, the relationship is upward sloping, meaning that more productive firms gain labor shares at the expenses of less productive ones.[20]

The contribution of firm demography to aggregate industry productivity is not affected by credit supply shocks during the financial crisis. The coefficient of interest is small and not statistically significant neither for the entry nor for the exit component across all specifications. It is worth clarifying that according to the MP decomposition the entry and the exit component refer to the contribution of entering and exiting firms to aggregate productivity growth, and

[20]Incidentally, this plot rationalizes the consistently positive contribution of the reallocation component highlighted in Figure 2.

Figure 4. Employment Growth, by Percentile of the Productivity Distribution



Note: Each dot shows the average employment growth of incumbent firms (y-axis) by the percentile of the productivity distribution (x-axis) measured at the beginning of each of the three subperiods displayed in the figure. The solid lines are calculated as a kernel-weighted local polynomial regressions.

not to the rate at which they enter or exit the market. In particular, the contribution of entry (exit) is given by the product of the entry (exit) rate and the average productivity difference between entering (exiting) and incumbent firms. Hence, our results should not be interpreted as showing that credit shocks do not affect the entry or the exit *rates*. They do not appear to significantly affect the *contribution* of firms entry and exit to aggregate productivity growth.

Overall, we fail to identify an effect on aggregate (labor) productivity, as a consequence of the two opposing forces exerted by average productivity and reallocation, which end up offsetting each other: a stronger negative supply shock reduces on average the productivity at the firm level, but at the same time it fosters a more efficient allocation of within-industry labor shares.

A natural extension of these results is to check whether they also hold in normal times. To do that, we focus on years 2000–07 (labeled as the pre-crisis period), that we have shown in Figure 2 to be a period of moderately increasing economic activity and expansionary bank lending conditions. We test Equation (7) on this different time

Table 9. Industry-Level Results: Pre-crisis Period (2000–07)

Dependent VARs	Independent VAR	(1)	(2)	(3)	(4)
Average Productivity	CSS_t	–0.079	0.113	–0.806	0.244
		(0.354)	(0.360)	(0.537)	(0.388)
Reallocation	CSS_t	–0.112	0.179	1.292**	–0.314
		(0.363)	(0.379)	(0.584)	(0.435)
Entry	CSS_t	–0.159	–0.239***	–0.203***	–0.204*
		(0.116)	(0.089)	(0.078)	(0.104)
Exit	CSS_t	0.368*	0.199	0.219	0.200
		(0.195)	(0.187)	(0.193)	(0.227)
Aggregate Productivity	CSS_t	–0.249	0.026	0.154	–0.317
		(0.359)	(0.401)	(0.769)	(0.459)
Year FE		Y	Y	Y	N
NACE Two-Digit FE		Y	Y	N	N
NACE Four-Digit FE		N	N	Y	N
Year*NACE Two-Digit FE		N	N	N	Y
Weighted		N	Y	Y	Y
Observations		1,239	1,239	1,239	1,232

Note: The table displays the estimates of the coefficient β in model (7). Each column uses a different set of fixed effects indicated at the bottom of the table and each row uses a different dependent variable, corresponding to each component of the MP decomposition. "Weighted" indicates that regressions are weighted using four-digit industry employment weights. Standard errors clustered at the industry (NACE four-digit) level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

sample; credit supply shocks are recalculated accordingly, using the banks' market shares in year 1999 to aggregate the shocks at the industry level.

The results, displayed in Table 9, show that before the crisis credit supply shocks did not significantly affect average productivity. This may reflect the possibility that in normal times firms are less financially constrained, with the consequence that demand factors may be more relevant in shaping the firms' behavior than the availability of bank credit. In the regressions on the reallocation term, the coefficient of interest is imprecisely estimated. If anything, a higher credit supply shock seems to foster an improvement in the reallocation term. Credit shocks seems to have a more robust effect on entry (third row), whose contribution to industry productivity growth worsens as a consequence of a higher credit supply shock. In light of Equation (4), this can be rationalized by thinking that looser credit conditions may both foster a higher entry rate (and therefore a greater mass of entering firms, ω_E) and allow relatively less productive firms to enter the industry (therefore lowering the average productivity of entrants, Φ_E). These effects, however, are not sizable enough to be show up in aggregate industry productivity, which even in this case is not significantly affected by the idiosyncratic credit supply shocks.

In Table 8 we already tested the robustness of our results to specifications including different sets of industry and time fixed effects. We now subject our findings to two additional robustness checks. The first concerns the definition of the credit shocks. As explained extensively in Section 4, we used predetermined weights to aggregate the bank shocks at the industry level, in order to avoid potential endogeneity issues associated with the contemporaneous banks' market shares. This concern is especially relevant when it comes to studying the effect of credit shocks on the reallocation component: the reallocation of workers across firms may affect the shares of credit if more productive firms are systemically matched with banks experiencing a higher (or lower) than average credit supply shock. We nonetheless test the robustness of our estimates to two additional definitions of credit shocks. The first fixes the aggregation weights further back in time, using values as of 2000; while on one hand, we may expect that these shares will reduce the informative content (and therefore the explanatory power) of the shocks, on the other hand, they allow us to reinforce the exogeneity claim with respect to the investigated phenomena. The second uses contemporaneous time-varying weights, which—as already explained—may potentially suffer from serious endogeneity problems. Results displayed in Table 10 show that the effects of credit shocks on average productivity are confirmed even under these two alternative definitions of bank lending shocks. Coefficients are also roughly similar in the specification using the fixed-weights shocks. The effects on the reallocation component remain negative across specifications, although slightly lower in size; when using time-varying weights, the coefficient becomes non-significant, with a p-value of 0.25. Essentially no effects on the demography terms and on total productivity are detected even under the alternative definitions of credit shocks.

The second robustness check concerns the timing of the effects. We test whether credit supply shocks have a lagged effect on each

Table 10. Robustness Check: Different Definitions of Credit Supply Shocks

Dependent Variables	Baseline	2000 Weights	Variable Weights
Average Productivity	1.244***	1.185***	0.782*
	(0.300)	(0.271)	(0.455)
Reallocation	–0.842**	–0.563*	–0.491
	(0.366)	(0.308)	(0.430)
Entry	0.072	0.003	0.128*
	(0.068)	(0.054)	(0.067)
Exit	–0.098	0.0100	0.022
	(0.104)	(0.080)	(0.120)
Aggregate Productivity	0.423	0.653	0.542
	(0.429)	(0.398)	(0.564)
Observations	1,416	1,416	1,416

Note: The table displays the estimates of the coefficient β in model (7) on each dependent variable, using different definitions of the credit supply shock. The baseline regression (column 1) uses the definition of credit supply shock in Equation (6); results in column 2 are obtained using a credit supply shock that aggregates the bank shocks according to their market shares in 2000; column 3 uses a credit supply shock that aggregates the individual bank shocks according to market shares varying every year. Year and sector (NACE two-digit) fixed effects included in all specifications. All regressions are weighted by the number of employees in each industry. Standard errors clustered at the industry (NACE four-digit) level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

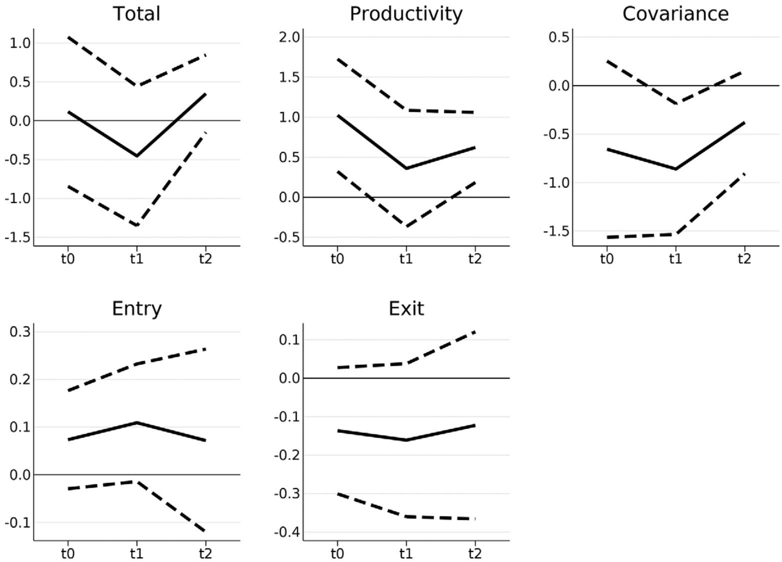
component of the MP decomposition. To this aim, we estimate the following distributed lag model based on our baseline model (7):

$$y_{jt} = \beta_0 * CSS_{jt} + \beta_1 * CSS_{j,t-1} + \beta_2 * CSS_{j,t-2} + \gamma_t + \delta_j + \varepsilon_{jt},$$

where y_{jt} is each term of the MP decomposition. The coefficient β_0 can be interpreted as the contemporaneous impact of the credit supply shock, while β_1 and β_2 are the effect one year and two years later, respectively.[21] The findings are shown in Figure 5. The effect

[21]We resort to a simple distributed lag model for two reasons. The first is that we aim at keeping this part of the analysis as simple as possible, as it should be understood as a cursory exploration of potential lagged effects of the credit

Figure 5. Lagged Effects of Credit Shocks



Note: The figure shows coefficients and confidence intervals of the coefficients of the following regression: $y_t = \beta_0 * CSS_t + \beta_1 * CSS_{t-1} + \beta_2 * CSS_{t-2} +$ fixed effects, where y_t is each term of the MP decomposition. The coefficient β_0 can be interpreted as the contemporaneous impact of the credit supply shock, while β_1 and β_2 are the effect one and two years later, respectively.

on average productivity is strong on impact, and then it becomes somewhat smaller (marginally not significant at $t-1$, significant at $t-2$). This points to some persistence in the effects of credit shocks on average firm-level productivity. The effect of credit shocks on the reallocation component becomes instead stronger, and significant, one year later. At $t-2$ it gets smaller, and statistically not significant. This suggests that the effect of credit shocks on the reallocation component dies out relatively quickly. The effects on the contribution of entry and exit are never statistically significant, instead, as shown in the baseline estimates.

shocks on the decomposition. Second, the serial correlation of the credit shocks is not large: the one between time t and $t-1$ is 0.38; the one between $t-1$ and $t-2$ 0.66; the one between t and $t-2$ is a mere 0.02. This suggests that estimating a simple lagged distributed model may be appropriate.

7. Industry Heterogeneity

To deliver a richer set of results and to incidentally reinforce our argument that tighter financial constraints act as a catalyst for the effects documented in our baseline estimates, we now turn to exploring whether our results are heterogeneous across industries. In Table 11, we focus on a wide array of industry-level characteristics that could be relevant in shaping the response of firms to a credit supply shock. In particular, we estimate our model interacting the credit supply shock with a dummy indicating industries located above and below the median value of each characteristic (measured as of 2007). To perform this test, we estimate Equation (7) with year and NACE two-digit fixed effects, weighted by the number of employees in the industry (the specification in column 2 of Table 8).

In the first and second panels we distinguish industries according to their share of collateralized debt and of tangible capital, respectively. These characteristics are correlated: industries with a lower share of tangible capital are those in which inputs are more easily redeployable; moreover, tangible capital can be easily collateralized by firms, allowing them to access external bank finance, thus alleviating credit constraints. The results show that the effects of negative credit shocks on average productivity and reallocation are concentrated in industries with a lower share of tangible capital and collateralized debt. The differences are statistically significant. This suggests that the availability of collateral or guarantees are crucial to hamper or exacerbate the harshness of a financial restriction: industries characterized by a lower share of collateralized debt suffer a drop in average within-firm productivity and experience a reallocation of labor shares from less to more productive units. Again, we find more pronounced effects in industries that are more likely to feature stronger credit constraints.[22]

The third panel shows how the effects of credit shocks are heterogeneous across industries with different levels of profitability, which we measure as the ratio of EBITDA to total assets (return on

[22]We have performed the same exercise using leverage as the heterogeneity dimension of interest. We found little difference between the industries above and below the median leverage. This is not in contrast with the results discussed so far, since leverage is not specific to bank debt, and therefore may be a poor proxy for credit constraints.

Table 11. Industry-Level Results: Sectoral Heterogeneity

	Below/Above Median	Average Productivity	Reallocation	Entry	Exit	Aggregate Prod.
Share of Collateralized Debt	Below (B)	1.282***	–1.043**	0.076	–0.098	0.298
		(0.304)	(0.494)	(0.072)	(0.137)	(0.586)
	Above (A)	–0.128	–0.169	–0.100	0.138	–0.253
		(0.624)	(0.457)	(0.126)	(0.158)	(0.557)
	B–A	1.410**	–0.874	0.176	–0.236	0.551
	pval. H0: B=A	0.044	0.195	0.226	0.259	0.497
Share of Tangible Capital	Below (B)	1.582***	–1.309***	0.112	–0.153	0.311
		(0.371)	(0.452)	(0.091)	(0.139)	(0.578)
	Above (A)	0.459	0.625	–0.099	–0.004	0.900
		(0.566)	(0.692)	(0.110)	(0.140)	(0.666)
	B–A	1.123*	–1.934**	0.211	–0.149	–0.589
	pval H0: B = A	0.099	0.020	0.142	0.448	0.505
Profitability (ROA)	Below (B)	1.489***	–1.368***	0.055	–0.059	0.217
		(0.343)	(0.512)	(0.098)	(0.148)	(0.590)
	Above (A)	1.184**	–0.069	–0.001	–0.054	0.986*
		(0.560)	(0.448)	(0.059)	(0.147)	(0.575)
	B–A	0.305	–1.298*	0.056	–0.005	–0.769
	pval H0: B=A	0.643	0.058	0.627	0.981	0.352
Import Competition	Below (B)	0.958*	–1.398**	0.218**	–0.230*	–0.451
		(0.502)	(0.641)	(0.104)	(0.120)	(0.678)
	Above (A)	1.370***	–0.524	0.039	–0.144	0.847*
		(0.343)	(0.416)	(0.067)	(0.137)	(0.503)
	B–A	–0.412	–0.874	0.179	–0.085	–1.298
	pval H0: B=A	0.499	0.255	0.149	0.640	0.126

(*continued*)

Table 11. (Continued)

	Below/Above Median	Average Productivity	Reallocation	Entry	Exit	Aggregate Prod.
Market Share of Top 20 Firms	Below (B)	1.345***	–0.391	0.034	0.105	1.031**
		(0.391)	(0.249)	(0.071)	(0.119)	(0.448)
	Above (A)	1.204**	–1.677**	0.115	–0.399**	–0.666
		(0.520)	(0.788)	(0.123)	(0.179)	(0.644)
	B–A	0.141	1.286	–0.081	0.505**	1.697**
	pval H0: B=A	0.829	0.122	0.570	0.020	0.032

Note: The table displays the estimates of the coefficients β_A and β_{B-A} of the following model: $y_{jt} = \beta_A * CSS_{jt} + \beta_{B-A} * CSS_{jt} D_j +$ fixed effects $+ \varepsilon_{jt}$, where D_j is a dummy variable equal to one if the industry j is below the median value of a certain variable of interest. The coefficient for the group of industries below the median is obtained by linear combination of β_A and β_{B-A}. The estimates are performed on different dependent variables, reported at the top of the column. Each panel displays the estimates obtained using a different variable of interest—measured as of year 2005—to define the dummy D_j. The p-value for the null hypothesis that the two groups have equal means is displayed in each panel. Import competition is defined as the ratio between imports and domestic absorption. All regressions are weighted by the number of employees in each industry; year and sector (NACE two-digits) fixed effects included. Standard errors clustered at the industry (NACE four-digit) level in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

assets).[23] With imperfect capital markets, a higher industry profitability allows firms to relax credit constraints by using internal finance (Fazzari, Hubbard, and Petersen 1987). While we do not find any significant difference in terms of average productivity between low- and high-profitability industries, the effects of credit shocks on the reallocation component are negative and significant only for less profitable industries, suggesting that in those industries credit shocks triggered a more intense reallocation of labor shares, due to tighter credit constraints among this group of firms.

In the fourth panel we classify industries according to the level of import competition, that is, the ratio between imports and domestic absorption. Import competition—in particular from developing countries—can affect productivity through two main channels. On the one hand, it can affect within-firm productivity by stimulating innovation and technological change (Bloom, Draca, and Van Reenen 2016); on the other hand, it can foster the reallocation of resources from the least to the most productive firms (Melitz 2003). The results show no statistically significant differences in the effects on average productivity: both are negatively affected by a credit supply restriction. Although the effects of the credit shock on the reallocation component is not statistically different, the point estimates in industries with import competition below the median are significant and almost three times larger: it's only in these industries—more sheltered from foreign competition and therefore potentially less efficient—that a credit restriction forces a reallocation of resources to more productive uses.

In the last panel we divide industries according to product market concentration. Following Autor et al. (2020), we measure industry concentration as the share of sales of superstar firms, defined as the 20 largest firms in each industry. The results show that credit shocks reduce average productivity in all industries, while the effect on reallocation is much higher in industries where the market shares are more concentrated among superstar firms. The difference in the coefficients is significant at the .12 level. Because superstars are likely to be the most productive and financially unconstrained firms within

[23]EBITDA is earnings before interest, taxes, depreciation, and amortization. It is a measure of operating profits.

industries, a negative credit supply shock is likely to have a negative impact only on small and unproductive firms, thus generating an increase in the employment share of superstars. The same is not true for average productivity; while superstar firms account for a large share of revenues and employment, they are very few in number, therefore their contribution to average productivity growth is negligible (it actually goes to zero as the number of firms in the industry become very large).

8. Local Labor Market Results

A natural extension to our results is to test the effects of credit shocks on the components of aggregate productivity growth within commuting zones (local labor markets) rather than within industries: on one hand, it can be argued that credit shocks may be localized in space, instead of affecting entire industries; on the other hand, narrower geographic areas may be the relevant observational unit to gauge the overall effect of a lending cut on labor (Huber 2018). We therefore repeat our empirical exercise using commuting zones ("sistemi locali del lavoro", SLL) as a unit of analysis. These geographical units are defined by Istat according to the degree of self-containment of the home-to-work commuting flows; conceptually, they are similar to the U.S. metropolitan statistical areas. The classification adopted in this work subdivides the Italian territory into 686 SLLs.

The empirical strategy is essentially the same as that used for the industry-level analysis discussed in Section 5. As shown in Table 12, the effects of an idiosyncratic variation in credit supply on within-SLL aggregate productivity mostly unfold through the contributions of average productivity and reallocation, as in our baseline within-industry exercise. The direction of the effects is also the same: when credit supply contracts, the average productivity term drops, to a large extent offset by the increase in the contribution of reallocation. The latter effect is marginally non-significant in the more demanding specifications including SLL fixed effects and region*year fixed effects (p-values 0.16 and 0.14, respectively). No effect is detected on the exit and entry components, as well as on aggregate within-SLL productivity. Overall, in a period of financial distress the consequences of a credit restriction can be spotted not only within narrowly defined industries but also within commuting zones, i.e.,

Table 12. SLL-Level Results

Dependent VARs	**Independent VAR**	**(1)**	**(2)**	**(3)**
Average Productivity	CSS_t	0.178***	0.153***	0.118***
		(0.042)	(0.036)	(0.028)
Reallocation	CSS_t	–0.107**	–0.101	–0.073
		(0.055)	(0.072)	(0.050)
Entry	CSS_t	0.015	0.000	0.009
		(0.010)	(0.007)	(0.011)
Exit	CSS_t	–0.024	–0.008	–0.016
		(0.017)	(0.018)	(0.018)
Aggregate Productivity	CSS_t	0.092	0.111	0.024
		(0.072)	(0.095)	(0.065)
Year FE		Y	Y	N
Region FE		Y	N	N
SLL FE		N	Y	N
Year*Region FE		N	N	Y
Observations		4,871	4,871	4,871

Note: The table displays the estimates of the coefficient β in model (7), where j indexes the local labor market (SLL). The specification shown in each column uses a different set of fixed effects indicated at the bottom of the table and each row shows specifications with a different dependent variable, corresponding to each component of the MP decomposition. All regressions are weighted by the number of employees in each SLL. Standard errors clustered at the SLL level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

geographical areas that are relevant from the point of view of both the propagation of the shocks and the reallocation of the labor force.

In the spirit of the previous section, we performed additional tests to verify whether these estimates also display some degree of heterogeneity across relevant characteristics of the SLLs. Results are shown in Table 13. The first panel distinguishes between SLLs that host (at least) an industrial district—according to the Istat definition—and those that do not. As a consequence of a lending cut, the latter experience both a sharper drop in average productivity and a more pronounced increase in the reallocation term with respect to industrial districts. Moreover, in non-district SLLs, credit restrictions also

Table 13. SLL-Level Results: Spatial Heterogeneity

	Features	Average Productivity	Reallocation	Entry	Exit	Aggregate Prod.
Industrial Districts	Non-district (ND)	0.215***	–0.149*	0.010	–0.043**	0.125
		(0.052)	(0.076)	(0.010)	(0.021)	(0.094)
	District (D)	0.067	0.040	0.015	–0.003	0.077
		(0.055)	(0.061)	(0.025)	(0.044)	(0.088)
	ND–D	0.148*	–0.189*	–0.004	–0.040	0.048
	pval H0: ND=D	0.051	0.054	0.878	0.407	0.709
Specialization	Below Median (B)	0.185***	–0.132**	–0.001	–0.023	0.057
		(0.049)	(0.063)	(0.011)	(0.019)	(0.069)
	Above Median (A)	0.131**	–0.038	0.045*	–0.022	0.188
		(0.061)	(0.125)	(0.026)	(0.048)	(0.204)
	B–A	0.054	–0.094	–0.046	–0.000	–0.131
	pval. H0: B=A	0.491	0.502	0.108	0.993	0.544
Export Openness	Below Median (B)	0.033	0.047	–0.003	–0.026	0.032
		(0.049)	(0.099)	(0.015)	(0.026)	(0.098)
	Above Median (A)	0.206***	–0.150**	0.020	–0.029	0.098
		(0.045)	(0.070)	(0.013)	(0.022)	(0.094)
	B–A	–0.172***	0.197	–0.023	0.003	–0.067
	pval H0: B = A	0.009	0.105	0.239	0.930	0.623
Share of Guaranteed Credit	Below Median (B)	0.218***	–0.164**	0.022	–0.013	0.106
		(0.049)	(0.075)	(0.015)	(0.026)	(0.114)
	Above Median (A)	0.025	–0.004	0.004	–0.033*	0.003
		(0.033)	(0.067)	(0.011)	(0.018)	(0.069)
	B–A	0.193***	–0.160	0.017	0.020	0.104
	pval H0: B=A	0.001	0.114	0.360	0.531	0.435

(*continued*)

Table 13. (Continued)

	Features	Average Productivity	Reallocation	Entry	Exit	Aggregate Prod.
Banks per Capita	Below Median (B)	0.229***	–0.197*	0.022	–0.028	0.064
		(0.061)	(0.101)	(0.016)	(0.030)	(0.112)
	Above Median (A)	0.103**	0.000	0.012	–0.027	0.124
		(0.040)	(0.058)	(0.010)	(0.018)	(0.095)
	B–A	0.126*	–0.197*	0.010	–0.002	–0.060
	pval H0: B=A	0.083	0.091	0.603	0.956	0.686

Note: The table displays the estimates of the coefficients β_A and β_{B-A} of the following model: $y_{jt} = \beta_A * CSS_{jt} + \beta_{B-A} * CSS_{jt}D_j +$ fixed effects $+ \varepsilon_{jt}$, where D_j is a dummy variable equal to one if the SLL j is below median value of a certain variable of interest (the same applies in the first panel, where D_j indicates the SLLs hosting an industrial district). The coefficient for the group of SLLs below the median is obtained by linear combination of β_A and β_{B-A}. The estimates are performed on different dependent variables, reported at the top of the column. Each panel displays the estimates obtained using a different variable of interest to define the dummy D_j. The p-value for the null hypothesis that the two groups have equal means is displayed in each panel. Specialization is proxied by the Herfindahl index computed over total employees at the sector two-digit level in 2007. Export openness is computed as the share of revenues from exporting activities in 2007. The share of guaranteed credit within each SLL is computed in 2001. Banks per capita are calculated as the ratio between the number of banks localized in the SLL and the population of the SLL in 2001. All regressions are weighted by the number of employees in each SLL; year and region (NUTS2) fixed effects included. Standard errors clustered at the SLL level in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

drive up the contribution of exiting firms to aggregate productivity, as a consequence of the increase in exit rates. This is coherent with the evidence of Finaldi Russo and Rossi (2001), who find that firms located in Italian districts display an advantage in terms of financial relations with the banking system, facing both a lower cost of credit and milder financial constraints. This implies that the cleansing effects of a credit crunch are much more apparent in non-district SLL, and operate through the channels of both reallocation and exit from the market.

The results on industrial districts are partially mirrored in the second panel, which groups SLLs according to their degree of sectoral specialization (as measured by the Herfindahl index calculated from market shares at the two-digit sector level). When credit shrinks, less specialized SLLs face a greater reduction of average productivity and a more sizable increase of reallocation with respect to specialized ones. This may be due on one hand to the higher financial constraints faced by less specialized areas (in analogy with the industrial districts case). On the other hand, it may be due to the possibility that less specialized SLLs display a greater scope for reallocation: effective credit shocks unevenly distribute across sectors within SLLs, therefore leaving room for a reallocation of labor shares from low-productivity firms in severely hit sectors to high-productivity firms in other ones; this channel may be less relevant for more specialized SLLs, where credit shock is more uniform across sectors and productivity levels potentially more uniform across firms.

The third characteristic that we consider is export openness, which we measure as exports over total sales. Exporters depend more on external financing because of the additional costs related to trade (e.g., higher working capital and fixed exporting costs); recent contributions in the literature have shown that negative shocks to credit reduce both the selection of firms into exporting (Manova 2013) and the volume of exports for firms that continue exporting (Paravisini et al. 2015). Consistent with these findings, our results show that the effects on average productivity are entirely concentrated on the SLLs characterized by a high level of export openness. The effects on the reallocation component are also substantially more pronounced in more export-oriented SLLs: if, within the same SLL, smaller exporters are more credit constrained than larger ones, a negative shock to credit could relatively favor the latter, both through the increase of the labor share employed at home and through the potential acquisition the smaller competitors' market shares on the foreign markets.

In the fourth panel we show that the effects of a credit restriction entirely unfold through the SLLs characterized by a low share of guaranteed credit. The argument is essentially the same as that outlined in Section 7 when discussing the role of the different degree of collateralization across industries.

Lastly, the bottom panel shows that the effects of a credit crunch are more sizable, both in terms of average productivity and in terms of reallocation, for SLLs characterized by a lower number of banks per capita. This captures the degree of substitutability across alternative funding strategies, and therefore to indirectly measure the financial constraints resting on the firms of the SLL. The results again confirm that the impact of credit shocks on the components of aggregate productivity growth are detected in areas in which firms are more likely to be financially constrained.

9. Conclusions

In this paper we study if and to what extent credit supply shocks affect aggregate labor productivity during a period of economic downturn. We rely on the approach proposed by Melitz and Polanec (2015) to break down the dynamics of aggregate productivity into four components—the variation of average firm productivity, the reallocation of resources towards more productive firms, the contribution of exit, and the contribution of entry—and we test the effect of credit supply shock on each of these components as well as on aggregate productivity. We exploit a unique data set on the universe of Italian manufacturing firms that allows us to fully measure the entry and exit of firms and the reallocation of workers. We isolate credit supply shocks applying the procedure proposed in Greenstone, Mas, and Nguyen (2020) on granular microdata from the Italian Credit Register.

Our findings show that a restriction in credit supply does not significantly affect aggregate productivity growth, but triggers important within-industry dynamics: on one hand, a negative credit supply shock hinders aggregate productivity growth by depressing firm-level productivity (because of the lower productivity growth of the incumbents); on the other hand, it fosters the reallocation of labor shares from less to more productive firms, thus contributing positively to aggregate labor productivity growth. We estimate a rather small and statistically insignificant effect of credit shocks on the contribution of entry and exit to productivity growth.

We find that the effects of credit shocks on the reallocation component are stronger in industries that are ex ante more likely to include financially constrained firms: those with a lower degree of collateralization, a lower share of tangible capital, and lower profitability. The impact is also stronger in sectors that have a greater scope for reallocation, such as those that are less exposed to import competition or that are more concentrated.

Finally, we show that results are qualitatively similar if we perform the same analysis within commuting zones (local labor markets), which may be the relevant unit of aggregation if we think that credit shocks may be localized in space and labor is reallocated geographically rather than within industries. All results are confirmed and the effects are stronger in commuting zones that have a lower share of guaranteed credit and for those with fewer banks per capita, supporting the idea that negative credit supply shocks have stronger effects in areas where financial constraints are more likely to be binding.

Appendix. The Within- and Between-Industry Components of the MP Decomposition

The Melitz and Polanec (2015) decomposition can be applied at different aggregation levels: the overall economy, an industry, or a geographical area, for example. The results obtained for larger aggregates can be re-expressed as a function of those obtained for narrower aggregation levels. To draw a parallel with the empirical exercise performed in this paper, suppose that we apply the MP decomposition in Equation (4) to J industries. For simplicity, also assume that firms don't switch industry across years. In what follows, the notation will be similar to the one adopted in Section 3, with the j subscript indicating the industry-level variables.

The average productivity term of the aggregate labor productivity growth can be re-expressed as a weighted average of the industry-level average productivity components:

$$\Delta\bar{\varphi}_S = \sum_{j=1}^{J} \frac{N_{Sj}}{N_S} \Delta\bar{\varphi}_{Sj}, \tag{A.1}$$

where N_{Sj} and N_S are the number of surviving firms (between any couple of years) in industry j and in the overall economy, respectively.

For the other terms of the decomposition, re-aggregation is not equally straightforward. Generally speaking, each of them can be expressed as the sum of an intra-industry (within) component and an inter-industry (between) component.

In the case of reallocation, the within-industry component is given by

$$\Delta\mathrm{Cov}_S^W = \sum_{j=1}^{J} \frac{N_{Sj}}{N_S} \Delta\mathrm{Cov}_{Sj}. \tag{A.2}$$

The between-industry one is instead equal to

$$\begin{aligned}\Delta\mathrm{Cov}_S^B = \sum_{j=1}^{J} \Bigg[& \left(\frac{L_{Sj2}}{L_{S2}} - \frac{N_{Sj}}{N_S}\right)(\Phi_{Sj2} - \Phi_{S2}) \\ & - \left(\frac{L_{Sj1}}{L_{S1}} - \frac{N_{Sj}}{N_S}\right)(\Phi_{Sj1} - \Phi_{S1})\Bigg],\end{aligned} \tag{A.3}$$

where L_{Sjt} and L_{St} are the number of employees in surviving firms at time t in industry j and in the overall economy, respectively. The within-industry term is a weighted average of the industry-level reallocation terms. The between-industry component is essentially the variation of an across-industry covariance between productivity and market shares.

The exit term can also be expressed as the sum of an intra- and an inter-industry term:

$$\mathrm{Exit}^W = \sum_{j=1}^{J} \frac{L_{j1}}{L_1} \omega_{Xj1}(\Phi_{Sj1} - \Phi_{Xj1}) \tag{A.4}$$

$$\text{Exit}^B = \sum_{j=1}^{J} \frac{L_{j1}}{L_1} \omega_{Xj1}[(\Phi_{Xj1} - \Phi_{Sj1}) - (\Phi_{X1} - \Phi_{S1})], \qquad (A.5)$$

where L_{j1} and L_1 are the number of employees at time 1 in industry j and in the overall economy, respectively. Again, the within term is a weighted average of the industry-level components, while the between one depends on the relative productivity of incumbents and exiting firms in sector j with respect to all other incumbents and exiting firms in the economy.

Similarly, the entry term can be expressed as the sum of

$$\text{Entry}^W = \sum_{j=1}^{J} \frac{L_{j2}}{L_2} \omega_{Ej2}(\Phi_{Ej2} - \Phi_{Sj2}) \qquad (A.6)$$

$$\text{Entry}^B = \sum_{j=1}^{J} \frac{L_{j2}}{L_2} \omega_{Ej2}[(\Phi_{Sj2} - \Phi_{Ej2}) - (\Phi_{S2} - \Phi_{E2})]. \qquad (A.7)$$

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